# Homework 1

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For this assignment, a Perceptron Learning Algorithm was implemented in MATLAB.

## Part 0: Creating the Data Set

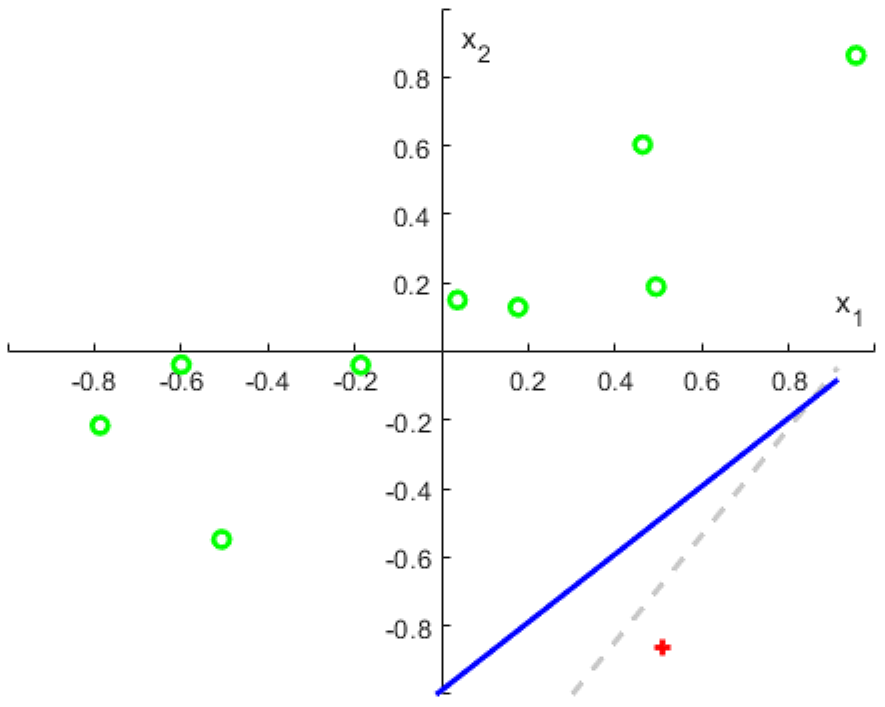
To create a data set, the provided `pla_getdata.m` is used, with an additional output `f` added, which returns the hidden target function:

```
N = 10; % data size
[x, y, f] = pla_getdata(-1, 1, 2, 11*N);
```

## Part 1: PLA and Testing

The PLA algorithm was implemented in `pla.m`, and a testing script `pla_test.m` was created for simple use. The weight vector `w` is preset as [0; 1; 1.5] and then adjusted by the PLA algorithm. Testing was done with two data sizes - N=10 and N=100 - and the average accuracy and iterations were found over 1000 runs **N=10** The results of this size varied wildly. With just 10 points in the training set, there's a higher likelihood that the training set does not accurately reflect the target function. In such cases, accuracy could be extremely low. The average accuracy across 1000 runs was calculated to be 89.5%, and the average number of iterations per hypothesis was 11.2. From this data, the approximate disagreement can be calculated to be 10.5%. Plots compare an example hypothesis `g` to the hidden function `f` with a training set.

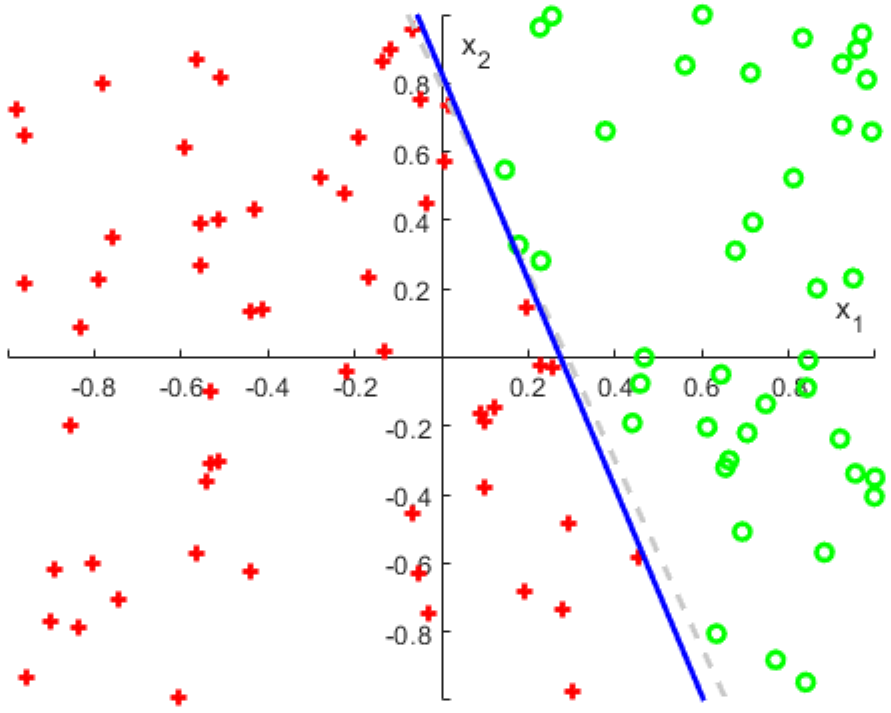
```
[x, y, g, f, i, a] = pla_test(10, 1000);
pla_plot_f(x, y, g, f); snapnow;
mi = mean(i)
ma = mean(a)
```



```
mi =

   10.4220


ma =

    0.8914
```

**N=100** Using this size resulted in a much more precise PLA, with an accuracy of 98.7% over 1000 runs, with an approximate disagreement of 1.3%. The cost of this is processing speed. Hypotheses took an average of 111.7 iterations to be judged as accurate enough.

```
[x, y, g, f, i, a] = pla_test(100, 1000);
pla_plot_f(x, y, g, f); snapnow;
mi = mean(i)
ma = mean(a)
```



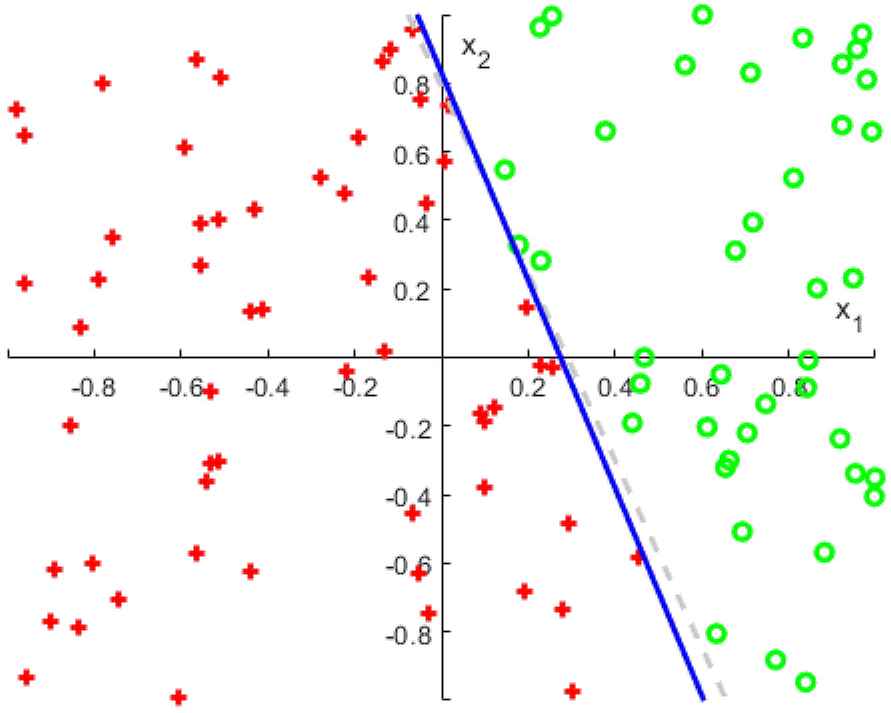
```
mi =

  114.4250


ma =

    0.9863
```

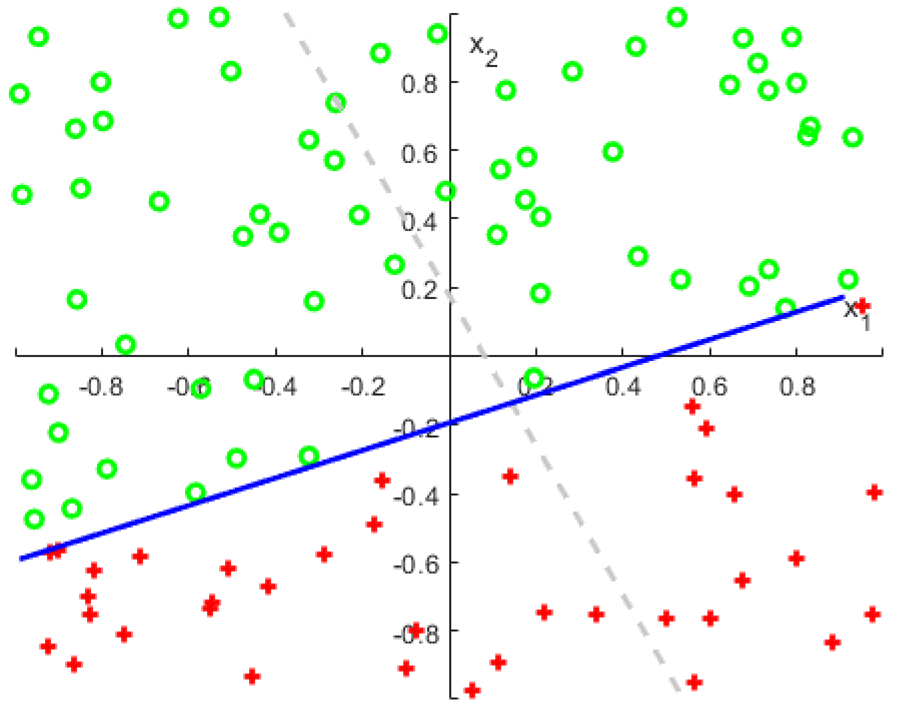
## Part 2: Modifying PLA

To further increase the PLA's accuracy, distance can be factored in when adjusting the weights of each hypothesis. Two more variables are thus added: distance `s(t)` and the learning factor $\eta$. For this, two new functions were created. The algorithm is trained with a set of 100 points and tested on a set of 10,000, and its iterations are limited to 1000 per guess. $\eta$ is tested for values of .0001, .01, 1, and 100. Again, plots compare an example hypothesis `g` to the hidden function `f` with a training set.

$\eta$=.001

```
[x, y, g, f, i, a] = pla_test_s(100, 1000, .0001);
pla_plot_f(x, y, g, f); snapnow;
mi = mean(i)
ma = mean(a)
```

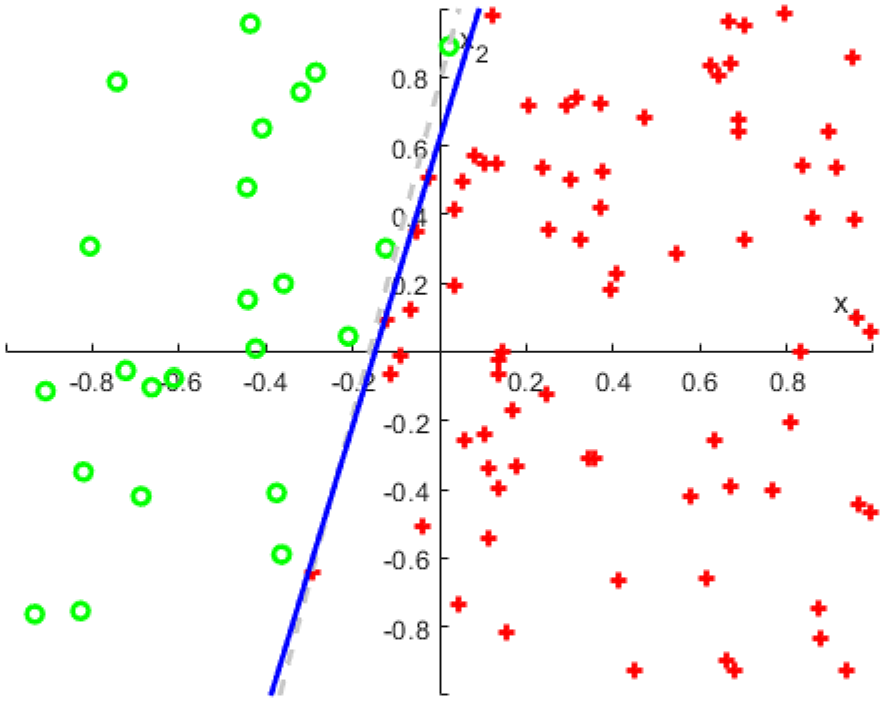

x2
x1
0.8
0.6
0.4
0.2
-0.2
-0.4
-0.6
-0.8
-0.8
-0.6
-0.4
-0.2
0.2
0.4
0.6
0.8


x2
x1
0.8
0.6
0.4
0.2
-0.2
-0.4
-0.6
-0.8
-0.8
-0.6
-0.4
-0.2
0.2
0.4
0.6
0.8

```
mi =

        1000


ma =

    0.4919
```

$\eta$=.1

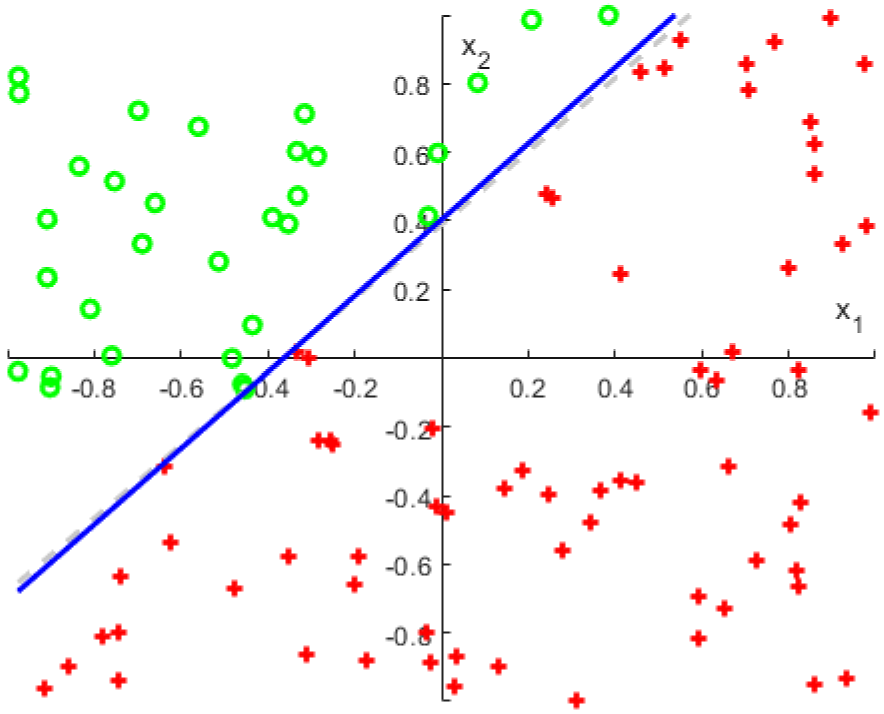
```
[x, y, g, f, i, a] = pla_test_s(100, 1000, .01);
pla_plot_f(x, y, g, f); snapnow;
mi = mean(i)
ma = mean(a)
```



```
mi =

  138.7820


ma =

    0.9920
```

$\eta$=1

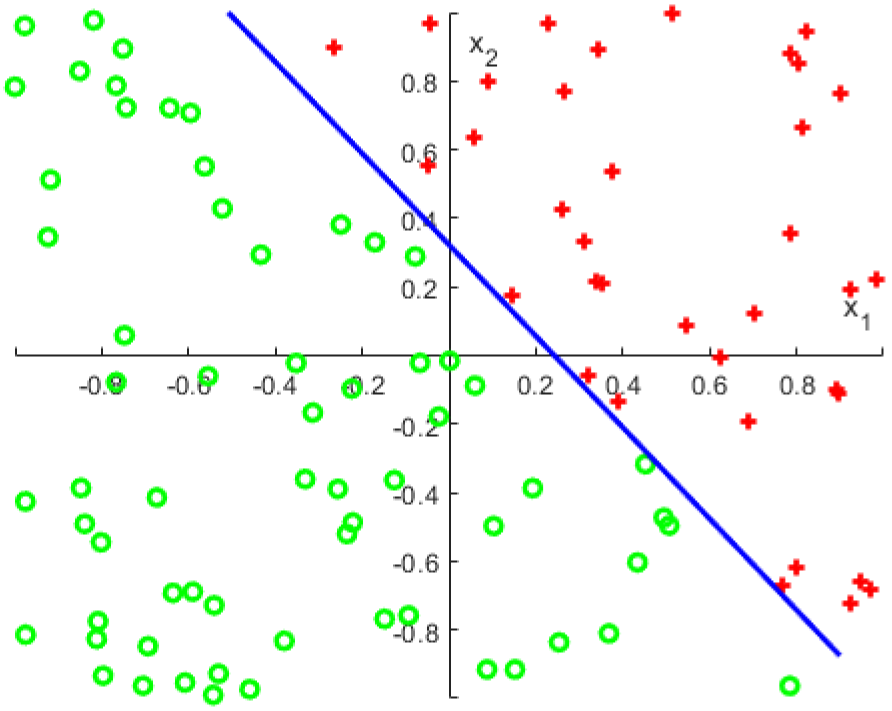
```
[x, y, g, f, i, a] = pla_test_s(100, 1000, 1);
pla_plot_f(x, y, g, f); snapnow;
mi = mean(i)
ma = mean(a)
```



```
mi =

  124.9850


ma =

    0.9784
```

$\eta$=100

```
[x, y, g, f, i, a] = pla_test_s(100, 1000, 100);
pla_plot_f(x, y, g, f); snapnow;
mi = mean(i)
ma = mean(a)
```



```
mi =

  945.7940


ma =

    0.6476
```

Limiting the iterations for this step is a necessary move. Especially for the case of $\eta$=.0001, the hypothesizing process just happens too slowly with so slow a learning rate. The new algorithm performed much more poorly than the simple PLA. I believe this is due to a mistake in the implementation, as it should theoretically be much more accurate.

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